Detection of Mobile Machine Damage Using Accelerometer Data and Prognostic Health Monitoring Techniques

Anya Getman, Christopher D. Cooper, Gary Key, Heng Zhou, and Nick Frankle, *Member, IEEE*

Abstract—**Caterpillar, Inc. and Frontier Technology, Inc. (FTI) are investigating prognostic health monitoring technologies for application to Caterpillar equipment. In particular, robust detection of mechanical damage in a wheel loader has been demonstrated via processing of high-speed, three-axis accelerometer data. Data collected with and without the damaged parts show distinctive signatures that are quantitatively separable. FTI's Pattern Recognition of Health (PRoH™) technology drives the signature generation and abnormality detection process through the use of data-driven techniques that estimate deviation from normal behavior.**

I. INTRODUCTION

THE early detection of changing conditions that precede an eventual system failure is a critical component of a condition-based maintenance (CBM) system and is referred to as prognostic health monitoring (PHM). Frontier Technology, Inc. (FTI) has developed and patented a technology to take data, predict their behavior based on known healthy system data, and determine the probability of abnormality based on the variance from the healthy prediction. This Pattern Recognition of Health (PRoH™) approach has been successfully demonstrated in a wide variety of systems including jet engines, oil platform turbines, heavy diesel military vehicles, and avionics systems. PRoH™ is the fundamental technology underlying FTI's NormNet™ software.

In previous work at Caterpillar, Inc., damage detection, in time to prevent catastrophic failure, was demonstrated on static testbeds [e.g., 1]. The next step is to evaluate technologies that can successfully operate on mobile platforms, so FTI was asked to examine data collected from heavy earth-moving machines. Ideally, their ProH technique should provide the ability to identify degrading conditions in advance of a system failure. For this pilot study, Caterpillar provided data from a wheel loader collected under a variety of operating conditions in two separate states: 1) with pristine mechanical components and 2) with multiple instances of induced mechanical damage. The damage state serves as a proxy for the types of degradation that would be expected during prolonged operation and that would precede more serious damage that could compromise the machine. The ability to distinguish between these two states (healthy and damaged) then is indicative of the ability of the technique to recognize precursors of system failure with enough warning that preventative or planned maintenance can occur, saving significant expense to the operator.

II. DATA COLLECTION

Caterpillar instrumented a wheel loader with a variety of sensors including two high-speed, three-axis accelerometers. The two accelerometers were placed at two locations on the underside of the machine, and are labeled "R" and "F". Data from the accelerometers were sampled at a 50 kHz rate (no anti-aliasing filter applied) and were collected along with engine speed, drive shaft torque, gear selection, and ground speed. This particular study concentrates on the "F" accelerometer and primarily utilizes the z-component of the data.

The wheel loader was assembled with multiple damaged transmission components and run through a series of operations at varying engine speeds and with multiple loads. Approximately 42 minutes of data were collected with the damaged components. The induced damage was equivalent to 3.3% of the contact surface area, which was the minimum detectable in an earlier test stand study using different techniques.

After completion of the damaged operations, the wheel loader was repaired by replacing the damaged components with pristine ones. The series of operations was repeated, again with varying engine speeds and multiple loads, for a total of approximately 31 minutes of data.

III. PROH™ BACKGROUND

PRoH™ is a data-derived prognostic health monitoring technology that has been developed by FTI for use in a wide variety of systems [2]. This approach employs stochastic methods, pattern recognition, and signal processing to perform continuous assessment of system performance in dynamic environments. Data from a variety of sensors collected under normal operating conditions are used to create a statistical model of healthy behavior. This model effectively captures the couplings among the variables that typically exist

---

This work was funded by Caterpillar, Inc.

A. Getman is with Caterpillar, Inc., Mossville, IL 61552 USA (phone: 309-578-3452; fax: 309-578-6014; e-mail: getman_anya@cat.com).

C. Cooper is with Frontier Technology, Inc., Beverly, MA 01915 USA (e-mail: ccooper@fti-net.com).

G. Key is with Frontier Technology, Inc., Beavercreek, OH 45431 USA (e-mail: gkey@fti-net.com).

H. Zhou is with Caterpillar, Inc., Mossville, IL 61552 USA (e-mail: zhou_heng@cat.com).

N. Frankle is with Frontier Technology, Inc., Beavercreek, OH 45431 USA (e-mail: nfrankle@fti-net.com).

due to true physical coupling. Environmental parameters may be used in the model generation process as well. In these cases, multiple normal models may be created that are conditioned upon these parameters. Environmental parameters thus represent proxies for different fundamental, physical modes of interaction within the system. The normal behavior model(s) is then applied to other data and will detect small variances that indicate abnormal conditions and potential system degradation. In an abnormal or degraded system, small physical changes work to adjust the statistical relationships among the variables. These variances in the relationships show up as a mismatch between the modeled behavior (based on the original physical interactions) and the measured behavior (based on the adjusted physical interactions. Thus variations in the physical system (such as degradation) are revealed as residuals between the measured and the modeled data.

This approach can be much more sensitive than simple threshold-based systems. Experience with other data sets [2] shows that while all individual variables may be within their normal ranges, the changed relationships among the variables may be readily detected. Furthermore, the pattern of the residuals among the multi-dimensional variable space is often characteristic of a particular fault or degradation mode. The patterns are recognized and classified using a vector quantization codebook technique based on the LBG or other algorithms [e.g. 3].

IV. DATA ANALYSIS

The analysis process started with the raw time-series data. While both accelerometers collected data in three axes each, the analysis here has focused on the z-component of the “F” accelerometer only (Fig. 1). The accelerometer data is more useful for monitoring in the frequency domain, so a 64 point fast Fourier transform was applied to create 33 useable frequency bands with a resolution of 781 Hz and a range of 0-25 kHz. An example of one of the resultant spectrograms (Fig. 2) is displayed with higher power represented by darker tones. The data from this two minute period were collected during normal operations where the engine speed varied from 608 to 2158 rpm. This set of variable, realistic conditions represents a challenge to the processing algorithm to properly identify all data during this time period as engaged in normal behavior.

Error! Reference source not found.Error! Reference source not found.

Training of the PRoH™ algorithm used two blocks of data from this undamaged equipment run. The first was representative of an idling engine, while the second was used while the engine was operating at higher speeds. The agreement of the model with the observed spectrogram is shown by a relative residual map (Fig. 3). This approach worked well, with the pair of conditional models successfully predicting the behavior of the undamaged machine. Some residual prediction error remains in the lowest frequencies, but these errors do not inhibit the ability to distinguish healthy from damaged systems.

Error! Reference source not found.

Data from the operations conducted using the damaged transmission components were modeled using the same conditional models derived from the healthy system data. The spectrogram of representative damaged system data (Fig. 4) is not qualitatively dissimilar from the undamaged system data (Fig. 2). The higher power in the 15-20 kHz range has more to do with the operating conditions than due to the damage itself. After applying the predictive model, the residuals that result are distinct from those seen in the undamaged system (Fig. 5). The pattern of predictive error is distinctive and appears to be related to the modes of induced damage.

Error! Reference source not found.

Error! Reference source not found.

After applying this technique to all of the undamaged and damaged data (excluding one set of undamaged data with different operational characteristics that will likely require a third model), statistics on the predictive ability of the technique can be constructed by taking the rms magnitude of the normalized residual vectors at each aggregated time sample. These rms magnitudes cluster into two distinct, separable populations (Fig. 6). Setting a threshold between these populations at 0.15 yields a false negative rate of 3.7% and a false positive rate of 6.5%.

Error! Reference source not found.

As noted above, applying a vector quantization technique to the residual data does an even better job of recognizing damaged data sets. An LBG vector codebook [4] was created with 64 nodes from a small sample of training data from both undamaged and damaged operations. The remaining data are then assigned to one of the nodes based on an approximate nearest neighbor distance. Figure 7 shows these assignments and the excellent discrimination between the undamaged and damaged data. Undamaged data are nearly always mapped properly as undamaged, and the average taken over a period of minutes generates a 100% correct identification. Damaged data are similarly mapped successfully, with one time period identified as questionable and the remainder (97%) confidently identified as damaged.

Error! Reference source not found.

V. CONCLUSIONS

The PRoH™ approach is successful at distinguishing between undamaged and slightly damaged systems. The small amount of induced damage in the wheel loader transmission is the type of precursor damage that is important to identify before more extensive (and expensive) transmission damage occurs. The ability of this technique to work under a variety of operating conditions and loads is critical to the ability to meet PHM goals for a CBM system. Vector quantization of residuals from PRoH™ predictions is particularly successful at recognizing slight damage at levels that have previously been difficult to confidently identify.

REFERENCES

[1] https://dspace.lib.cranfield.ac.uk/bitstream/1826/984/3/Adaptive%20vibrarion%20condition%20monitoring-gearboxes-2005.pdf

[2] N. Frankle and R. Shroder, Pattern Recognition Of Health - Data Derived Prognostic Health Management, Proceedings of the 62nd Meeting of the Society for Machinery Failure Prevention Technology, Virginia Beach, VA April 7, 2008.

[3] S. Arya and D. Mount, `"Algorithms for fast vector quantization," Proc. of DCC '93: Data Compression Conference}, eds. J. A. Storer and M. Cohn, IEEE Press, 1993, 381--390.

[4] http://research.sun.com/vlsi/pubs/00227469.pdf